Recent Ensemble Smoother Applications: Data-Space Inversion and Deep Learning for Facies Models

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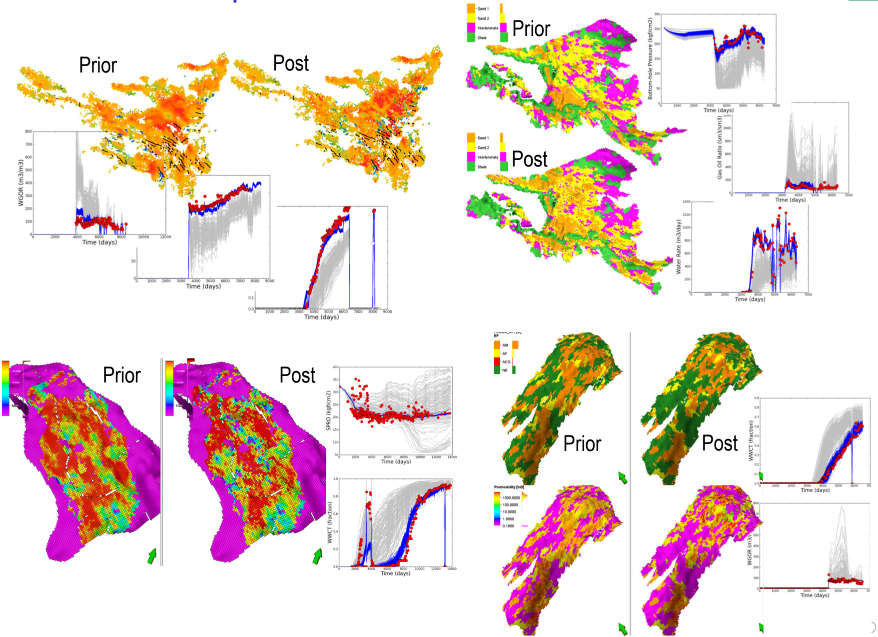
Outline

ES-MDA

- Reservoir history matching is a parameter-estimation problem.
- Simulation restarts required by EnKF (sequential data assimilation) are time-consuming:
  - Convergence problems in the reservoir simulations.
  - Very slow in clusters.
- ES is faster and simpler. But it does not match data sufficiently well.
- ES-MDA conciliates advantages of ES with better data matches: truly black-box and highly parallelizable.

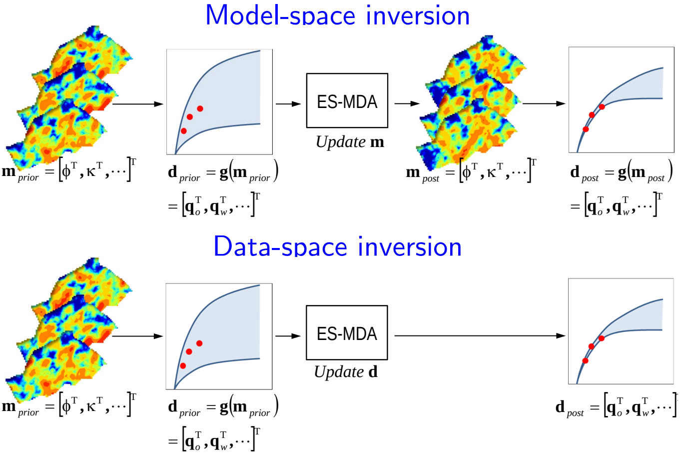
ES-MDA is in Operational Use



Outline

Data-Space Inversion*

- Inspired in the work from Sun and Durlofsky (2017)[1].
- Apply ES-MDA to updated directly the production profiles from a prior ensemble.

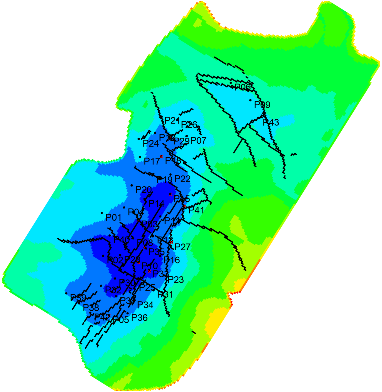


*Work with Mateus M. Lima (Petrobras) and Carlos E.P. Ortiz (UENF).

[1] Sun, W., Durlofsky, L., *A New Data-space Inversion Procedure for Efficient Uncertainty Quantification in Subsurface Flow Problems*, Math Geosci (2017).

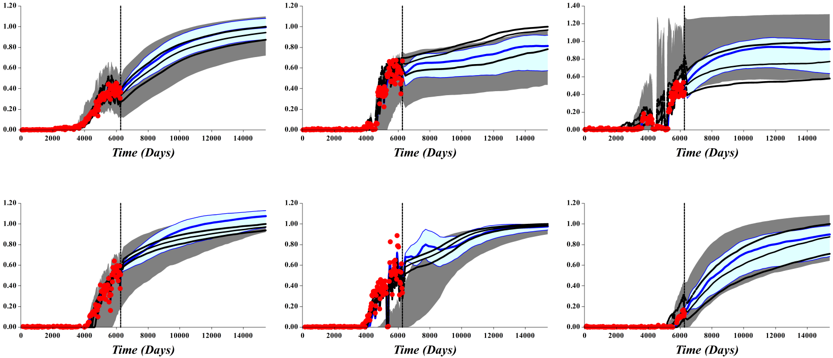
DSI – Field Case[2]

- Offshore turbidite Reservoir in Campos Basis.
- 18 years of production through 43 wells.
- Ensemble size: 500.
- Localization:
  - Space = 2 km.
  - Time = 6000 days.



[2] Lima, M.M.; Emerick, A.A. and Ortiz, C.E.P, *Data-Space Inversion with Ensemble Smoother*, arXiv:1903.09576 [math.NA] (2019).

Field Case – Water Production Rate



red dots: observed data

gray: prior (p10, p90)

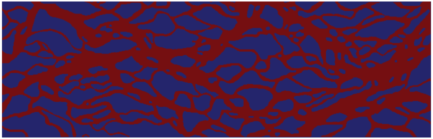
black: ES-MDA – model-space inversion (p10, p50, p90)

blue: DSI-ESMDA – data-space inversion (p10, p50, p90)

Outline

Facies Parameterization using Deep Learning*

- Updating channelized facies models is still a major challenge with ensemble data assimilation.



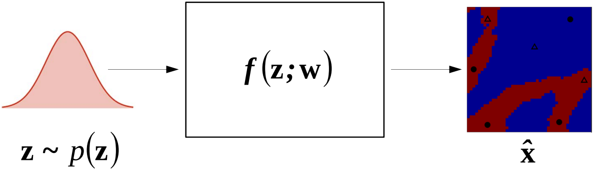
- Deep Learning (DL) emerged in the last decade as powerful technics for learning complex data representations[3].

*Work with Smith C. Arauco and Marco Aurélio Pacheco (PUC-Rio).

[3] Goodfellow, I., Bengio, Y. and Courville, A., *Deep Learning*, MIT Press (2016).

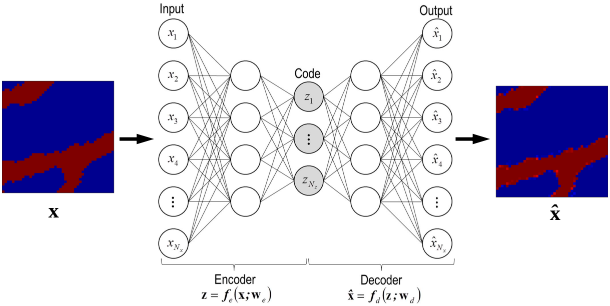
Generative Models

- Machine learning methods designed to generate samples from complex (and often with unknown closed form) probability distributions in high-dimensional spaces.
  - We would like to generate samples $\mathbf{x} \sim p(\mathbf{x})$.
  - We construct a deterministic function $\boldsymbol{f}(\mathbf{z};\mathbf{w})$ parameterized by $\mathbf{w}$, which receives a random argument $\mathbf{z} \sim p(\mathbf{z})$.
  - $\boldsymbol{f}(\mathbf{z};\mathbf{w})$ is modeled as a neural network, trained with a set of data points $\mathbf{x}_i$ such that if we provide $\mathbf{z} \sim p(\mathbf{z})$, it generates $\widehat{\mathbf{x}} \sim p(\mathbf{x}|\mathbf{z};\mathbf{w})$ which resembles samples from $p(\mathbf{x})$.



Autoencoders

- Combination of two neural networks:
  - Encoder: $\mathbf{z} = \boldsymbol{f}_e(\mathbf{x}; \mathbf{w}_e)$
  - Decoder: $\widehat{\mathbf{x}} = \boldsymbol{f}_d(\mathbf{z}; \mathbf{w}_d)$
- Training: find $\mathbf{w}_e$ and $\mathbf{w}_d$ that minimizes the reconstruction error, e.g., $\|\mathbf{x} - \widehat{\mathbf{x}}\|^2 = \|\mathbf{x} - \boldsymbol{f}_d(\boldsymbol{f}_e(\mathbf{x}; \mathbf{w}_e); \mathbf{w}_d)\|^2$.
- Autoencoders can be seen as nonlinear generalizations of PCA.



Variational Autoencoder (VAE)[4]

- For given training data, $\mathbf{x}$, we want to design a neural network by maximizing $p(\mathbf{x})$ with respect to a set of learnable parameters $\mathbf{w}$.

$$p(\mathbf{x}) = \int_{\mathbf{z}} \underbrace{p(\mathbf{x}|\mathbf{z})}_{\text{generative model}} \overbrace{p(\mathbf{z})}^{\text{prior}} d\mathbf{z} = \mathrm{E}_{\mathbf{z}\sim p(\mathbf{z})}\left[p(\mathbf{x}|\mathbf{z})\right].$$

- One alternative for training is to use Monte Carlo:
  - Sample a set of $\mathbf{z}_i \sim p(\mathbf{z})$ and compute $p(\mathbf{x}) \approx \frac{1}{N}\sum_i p(\mathbf{x}|\mathbf{z}_i)$.
  - Apply gradient ascent to maximize $p(\mathbf{x})$ with respect to $\mathbf{w}$.
- It won't work if $\mathbf{x}$ is high-dimensional (we need too many samples $\mathbf{z}_i$).
- Variational inference: introduce another (easy to sample) distribution $q(\mathbf{z}|\mathbf{x})$ and determine the parameters of q such that it generates samples $\mathbf{z}_i$ corresponding to high probability regions of $p(\mathbf{x}|\mathbf{z})$.

[4] Kingma, D.P. and Welling, M., *Auto-Encoding Variational Bayes*, arXiv:1312.6114 [stat.ML] (2013).

Variational Autoencoder (VAE)

- Instead of maximizing

$$p(\mathbf{x}) = \mathrm{E}_{\mathbf{z}\sim p(\mathbf{z})}\left[p(\mathbf{x}|\mathbf{z})\right]$$

we maximize

$$\widehat{p}(\mathbf{x}) = \mathrm{E}_{\mathbf{z}\sim q(\mathbf{z}|\mathbf{x})}\left[p(\mathbf{x}|\mathbf{z})\right]$$

- The trick is to use a well-known result from variational inference:

$$\overbrace{\ln p(\mathbf{x})}^{\text{log-evidence}} - \underbrace{\mathcal{D}_{\mathrm{KL}}\left[q(\mathbf{z}|\mathbf{x})||p(\mathbf{z}|\mathbf{x})\right]}_{\text{error in the approximation}} = \underbrace{\mathrm{E}_{\mathbf{z}\sim q}\left[\ln p(\mathbf{x}|\mathbf{z})\right] - \mathcal{D}_{\mathrm{KL}}\left[q(\mathbf{z}|\mathbf{x})||p(\mathbf{z})\right]}_{\text{lower bound for the log-evidence}}$$

where $\mathcal{D}_{\mathrm{KL}}[q||p]$ is Kullback–Leibler divergence of q with respect to p.

- Instead of maximizing $\ln p(\mathbf{x})$ we can maximize its lower bound.

Variational Autoencoder (VAE)

- Mean field approach: select $q(\mathbf{z}|\mathbf{x}) = \mathcal{N}([\mu_1, \ldots, \mu_{N_z}]^\top, \mathrm{diag}[\sigma_1^2, \ldots, \sigma_{N_z}^2]^\top)$ and $p(\mathbf{z}) = \mathcal{N}(\mathbf{0}, \mathbf{I})$.
- During training, we minimize the loss function

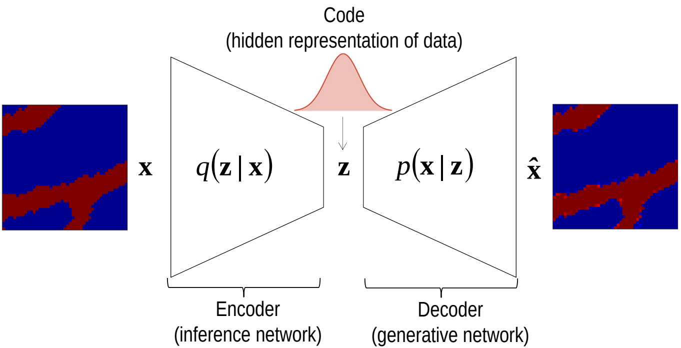
$$\mathcal{L}(\mathbf{x}) = \underbrace{\mathcal{L}_{\mathrm{RE}}(\mathbf{x})}_{\text{reconstruction error}} + \underbrace{\mathcal{D}_{\mathrm{KL}}\left[q(\mathbf{z}|\mathbf{x}) \| p(\mathbf{z})\right]}_{\text{regularization term}}$$

where

$$\mathcal{L}_{\mathrm{RE}}(\mathbf{x}) = -\frac{1}{N_x}\sum_{i=1}^{N_x}\left[x_i \ln(\widehat{x}_i) + (1 - x_i)\ln(1 - \widehat{x}_i)\right]$$

$$\mathcal{D}_{\mathrm{KL}}\left[q(\mathbf{z}|\mathbf{x}) \| p(\mathbf{z})\right] = \frac{1}{2}\sum_{i=1}^{N_z}\left(\mu_i^2 + \sigma_i^2 - \ln\left(\sigma_i^2\right) - 1\right)$$

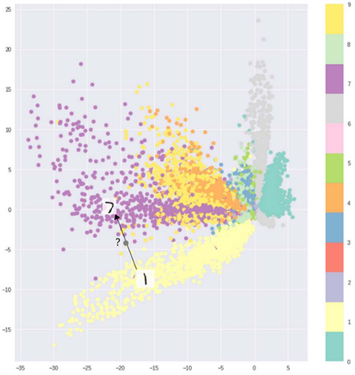
Variational Autoencoder (VAE)



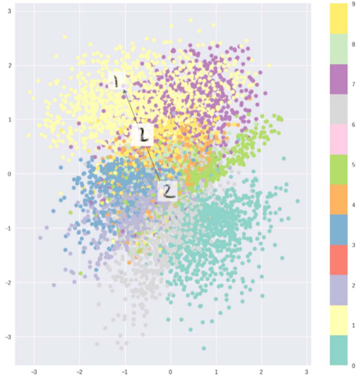
- $q(\mathbf{z}|\mathbf{x})$ encodes $\mathbf{x}$ in $\mathbf{z}$.
- $p(\mathbf{x}|\mathbf{z})$ decodes $\mathbf{z}$ in $\mathbf{x}$.
- Minimization of $\mathcal{L}_{\mathrm{RE}}(\mathbf{x})$ makes $\widehat{\mathbf{x}}$ to resemble $\mathbf{x}$.
- Minimization of $\mathcal{D}_{\mathrm{KL}}\left[q(\mathbf{z}|\mathbf{x})\|p(\mathbf{z})\right]$ pushes $q(\mathbf{z}|\mathbf{x})$ to be similar to $\mathcal{N}(\mathbf{0},\mathbf{I})$.

- Example MNIST (handwritten digits) dataset[5,6].
- VAE generates a more continuous latent representation (easier to interpolate).

Autoencoder



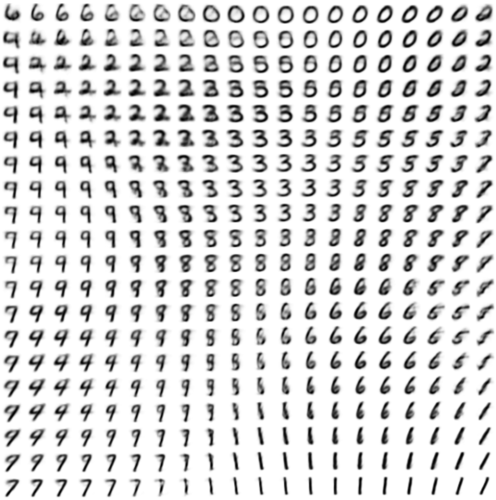
Variational autoencoder



[5] LeCun, Y., Cortes, C., and Burges, C.J.C., *The MNIST Database of Handwritten Digits*, `http://yann.lecun.com/exdb/mnist/`

[6] Shafkat, I., *Intuitively Understanding Variational Autoencoders*, `https://towardsdatascience.com/intuitively-understanding-variational-autoencoders-1bfe67eb5daf`

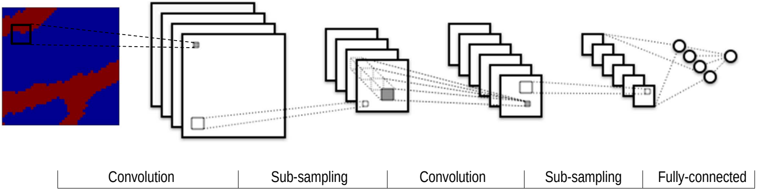
- Visualization of MNIST data with a two-dimensional latent space.
- VAE learned the data manifold[4].



[4] Kingma, D.P. and Welling, M., *Auto-Encoding Variational Bayes*, arXiv:1312.6114 [stat.ML] (2013).

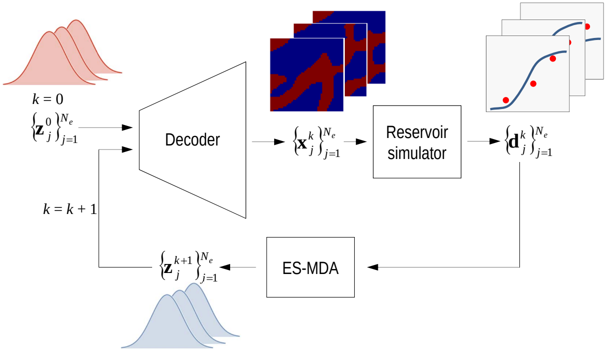
Convolutional Network[7]

- Standard fully-connected neural nets do not scale well for high-dimensional data $\mathbf{x}$.
- Convolution layers are specialized in data with grid structure such as images and time series.
- They provide a more efficient feature extraction by reducing the number of training parameters (weights in the filters).



[7] LeCun, Y. *Generalization and Network Design Strategies*. Tech report, University of Toronto (1989).

ES-MDA-CVAE[8]



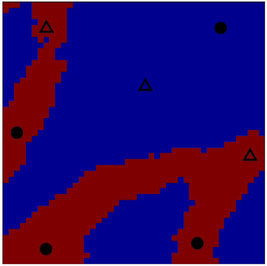
- After the CVAE is trained, we use ES-MDA to update the latent variables and the decoder to reconstruct facies.

[8] Canchumuni, S.W.A., Emerick, A.A. and Pacheco, M.A.C., *Towards a Robust Parameterization for Conditioning Facies Models Using Deep Variational Autoencoders and Ensemble Smoother*, Comput & Geosci (2019).

Test Case 1

- Two-facies model generated with *snesim*[9].
- 45×45 gridblocks.
- Constant permeability for each facies:
  - Channel: 5000 mD.
  - Background: 500 mD.

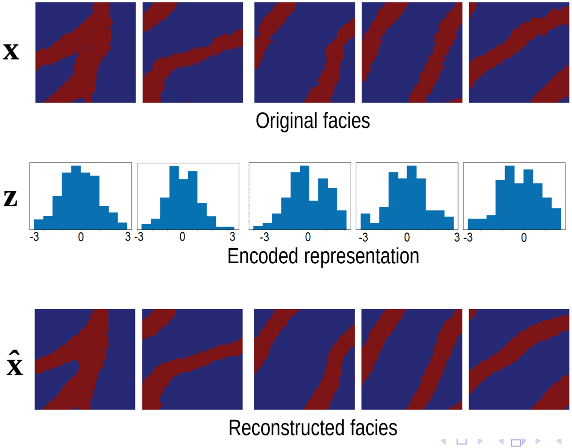
Reference



[9] Strebelle, S., *Conditional Simulation of Complex Geological Structures Using Multiple-point Statistics*, Math Geo (2002).

Test Case 1 – Training Results

- Training set: 24000 realizations. Validation set: 6000 realizations.
- 13 minutes in a cluster with four GPUs (NVIDIA TESLA P100).
- Reconstruction accuracy: 96.7%.

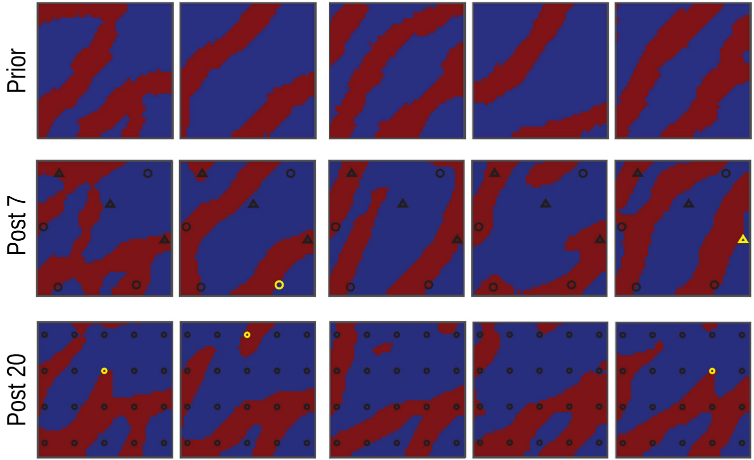


Test Case 1 – Testing the Decoder

- Generated a new realization by sampling $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$.
- Added small random perturbations: $\mathbf{z}^{k+1} = \mathbf{z}^{k} + \delta\mathbf{z}$, where $\delta\mathbf{z} \sim \mathcal{N}(\mathbf{0}, 0.1 \times \mathbf{I})$.

Test Case 1 – Data Assimilation (Facies Data)

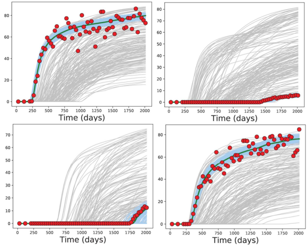
- MDA iterations: 4.
- Ensemble size: 200.

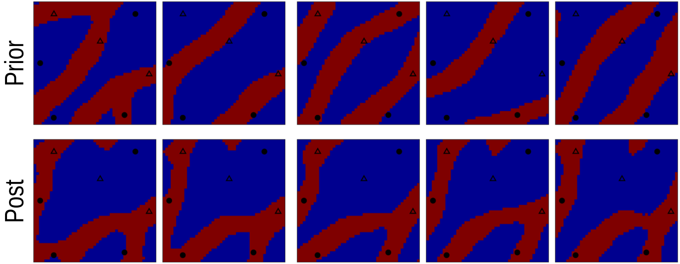


Test Case 1 – Data Assimilation (Production Data)

- Oil and water production data.
- MDA iterations: 4.
- Ensemble size: 200.

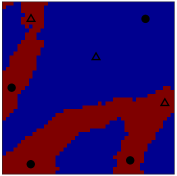
Water rate



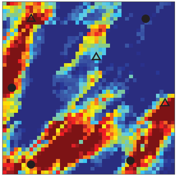


Test Case 1 – Comparison with Previous Results

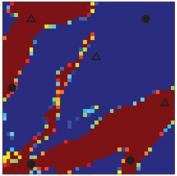
Reference



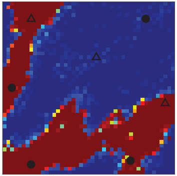
ES-MDA



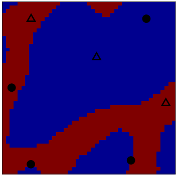
ES-MDA-OPCA[10]



ES-MDA-DBN[11]



ES-MDA-CVAE



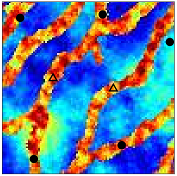
[10] Emerick, A.A., *Investigation on Principal Component Analysis Parameterizations for History Matching Channelized Facies Models with Ensemble-based Data Assimilation*, Math Geosci (2017).

[11] Canchumuni, S.W.A., Emerick, A.A. and Pacheco, M.A.C., *History Matching Channelized Facies Models using Ensemble Smoother with a Deep Learning Parameterization*, ECMOR (2018).

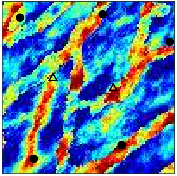
Test Case 2

- Two-facies model generated with *snesim*.
- 100×100 gridblocks.
- Simultaneous update of facies and permeability.
- Training: 32000, validation: 8000.
- Training time: 42 minutes*.
- Ensemble size: 200, MDA iterations: 20.

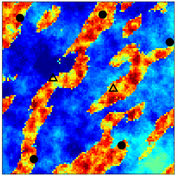
Reference



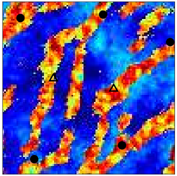
ES-MDA



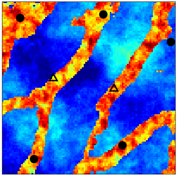
ES-MDA-OPCA



ES-MDA-DBN



ES-MDA-CVAE

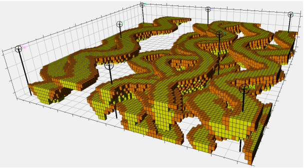


* Cluster with 4 GPUs (NVIDIA TESLA P100).

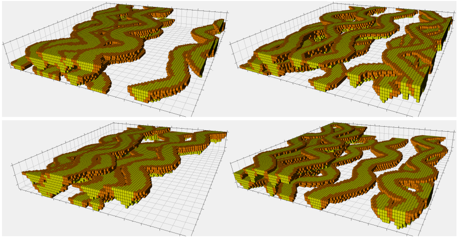
Test Case 3

- 3D channels (object-based simulation[12]).
- 3 facies: channel, levee and background.
- $100 \times 100 \times 10$ gridblocks.
- Training: 40000, validation: 10000.
- Training time: 49 hours*.
- Ensemble size: 200, MDA iterations: 20.

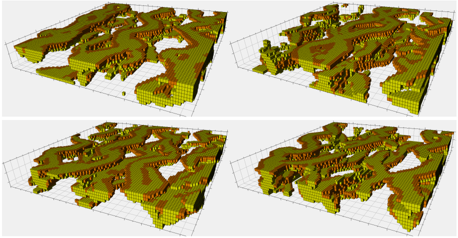
Reference



Prior



ES-MDA-CVAE

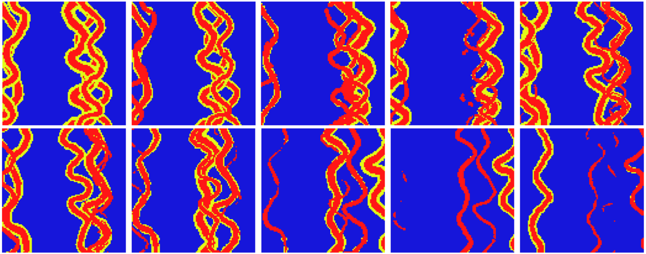


[12] Deutsch, C.V. and Journel, A.G. *GSLIB: Geostatistical Software Library and User's Guide*, Oxford University Press (1998).

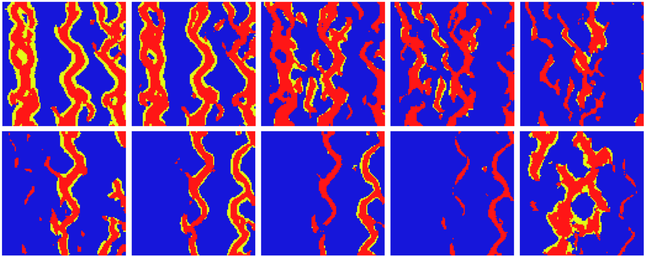
* Cluster with 4 GPUs (NVIDIA TESLA P100).

Test Case 3

Prior



ES-MDA-CVAE



Final Comments

- Data-space inversion:
  - Straightforward to apply.
  - It may serve as a first approximation.
  - It may be an useful for models with very complex geological description.
- Deep learning parameterization:
  - Promising results for facies models.
  - So far we tested only in small models ($\sim 10^4$–10^5 gridblocks).
  - It is unclear if it is going to be feasible in large-scale models ($> 10^6$ gridblocks).
  - Current implementation does not allow distance-based localization.

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